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Abstract

Datasets of schools or hospitals often include an urban–rural divide drawn by government. Such partition is typically determined by subjective thresholds for a few variables, such as access to transportation and local population size, leaving aside relevant factors despite data availability. We propose to measure 'remoteness' by mapping a comprehensive set of covariates onto a scalar, and define an objective score of remoteness using a standard selection model. We apply the proposed method to data from Taiwanese public elementary schools. Our method replaces 35% and 47% respectively of the current official list of 'remote' and 'extra-remote' campuses, shifting the remoteness designation to those furthest from train stations, having the highest teacher vacancy percentages, and located in the least populous areas with the least well-educated populations. The campus- and district-level variables used are publicly available and periodically updated in most advanced economies, and the statistical model can be easily implemented.

Keywords: selection model, remoteness score, rural education, rurality classification

Measuring Remoteness Using a Data-Driven Approach

Government agencies and other organizations that wish to alleviate disparity in resources between urban and rural areas must begin with some definition of ‘rural’ or ‘remote.' For instance, the US Census Bureau defines ‘rural’ as population, housing, or territory not included within an urban area, with ‘urban’ tracts drawn according to population density, land use, and distance from nearby stations or urban areas and by applying a population threshold to include areas around urban centers (Ratcliffe, Burd, Holder, & Fields, 2016). Such delineations require constant updates to reflect progress in urbanization. However, revisions to the urban/rural classification of districts are not always due to changes in underlying behaviors of land use or residence, and often instead reflect the discontinuous nature of the classification process. As a result, a shift in the discontinuous thresholds cannot fully justify a reallocation of resources.

A notable example is a change in the rural school classification made by the US National Center for Educational Statistics (NCES) in 2006. The NCES classifies rural schools based on population size and distance to a populous area. As the 2000 Census advanced its ability to geocode schools and other locations, the NCES replaced the 1980 locale codes with a finer and more accurate classification using the 2000 Census (Geverdt & Phan, 2006). This adjustment resulted in 2,878 public elementary/secondary schools switching from nonrural to rural classification and 2,418 schools switching from rural to nonrural classification. The impact of the policy change was large as the shift accounted for about 18% of schools that were classified as rural for the 2003–04 school year.

Apart from the classifications drawn from the US Census, other systems have been developed by the US federal government, each serving a different purpose.[1] Recently, distance education and telehealth projects have been taking place worldwide, targeting rural, remote, or isolated areas (hereafter 'remote areas'). Similar classifications have emerged in many countries, including Australia, China, Japan, South Korea, and Taiwan.[2]

One prerequisite for such policies or projects to be successful is an accurate and up-to-date classification for remote areas. Conventional methods of classification impose thresholds on local population size or distance to populous areas. However, the thresholds are somewhat ad hoc and updated more slowly than the speed of aging or urbanization (DeYoung, 1987; Greenough & Nelson, 2015). The threshold design includes few dimensions in local demographics and, most importantly, little information about the policy targets. For example, eligibility to the US Department of Education's Small, Rural School Achievement Program (SRSA) is determined by a set of thresholds on four variables: rurality status (defined by state government agencies), population density, the number of students, and the NCES classification. These thresholds ignore disadvantages in the learning process of students in rural areas, such as minority status, low parental income, or low parental education, which might require federal assistance through the SRSA. If schools were to lose access to the SRSA due to adjustments in the NCES school locale codes, the loss might not necessarily represent the lack of necessity for federal assistance; instead, it is more likely to reflect changes in the way the locality data are managed by the federal government.

To address these issues, we model the official selection of locations (e.g. school campuses) into the remoteness classification as a latent index crossing a data-driven threshold, where the latent index is interpreted as the expected net social benefit of selection into the remoteness classification. The data-driven threshold is estimated with a standard probit model and a comprehensive set of characteristics for each school campus (e.g., the speed of aging, the fraction of minority students, and the average income and education levels in the district). This approach assigns a ‘remoteness score’ to each campus, which is the propensity score or the estimated probability of being officially selected into the remoteness classification. Classification of remote schools can be performed by setting thresholds along the estimated index of remoteness, conditional on budget constraints.

Using data from all 2,606 public elementary school campuses in Taiwan, the proposed method reclassifies school campuses into the ‘remote,' ‘extra-remote,' or ‘not remote’ categories. Our method replaces 35% and 47% respectively of the current official list of remote and extra-remote campuses, shifting the remoteness designation to school campuses that are furthest from local train stations, have the highest unmet demand for full-time teachers, and are located in areas with the poorest, least-educated, and fastest-aging populations.

Any remoteness index should be adjusted over time because of the rapid aging of the population and urbanization. We use district-level data that are publicly available and updated periodically in most of the world’s advanced economies, such as geographic information (that can be obtained from online services) and demographic data (that can be downloaded from government websites). Our remoteness index improves on existing systems through expanding the set of information from which classifications are drawn and because of its applicability in a wide range of contexts.

The rest of the paper is organized as follows. The next section provides some background and a literature review that pull together the existing work on remoteness classifications and current trends in the development of methods. We propose a data-driven approach to classifying remoteness and present a model that motivates the construction of the remoteness score. Then we describe our data, show the results, and conclude.

Background and literature review

In most countries, governments typically draw a rural–urban divide to allocate resources. The need arises not necessarily because of issues in budget management, but rather because of underlying conditions that require special scrutiny, with examples in fields such as education (Greenough & Nelson, 2015; Kettler, Puryear, & Mullet, 2016; Puryear & Kettler, 2017) and health care (Clark et al., 2012). Kyrst, Kotok, & Bodovski (2015) reviews research on rural-urban disparities in education.

There are various approaches to the problem, ranging from defining rural areas according to cultural characteristics and historically defined constructs (Bealer, Willits, & Kuvlesky, 1965), to empirical definitions such as population density or distance from urban areas (Isserman, 2005). The potential quality improvement at stake in defining what is rural can be profound. For instance:

- *The World Inequality Database on Education (WIDE).* The database, created by UNESCO, portrays inequality in education in each country between different gender, places, wealth level, ethnicities, and religions. It is compiled by pooling education and survey data from various sources such as the Trends in International Mathematics and Science Study (TIMSS) and national household surveys. Based on the WIDE, the UNSECO has observed that rural youths have lower literacy compared to their urban counterparts (UNESCO, 2016). However, international comparisons such as the TIMSS samples schools with weights proportional to the size of their student body, with thresholds that exclude schools that are deemed to be too small (LaRoche, Joncas, & Foy, 2016). Such a sampling scheme is essential for providing an unbiased measurement of students' ability across a country, however as students living in rural areas are more likely to attend smaller schools and schools that fall outside the cutoff for sampling, the rural student sample in data sets from large international comparisons are both too small and truncated. Thus, the sampling scheme that provides an unbiased measurement for entire countries could lead to biased comparisons between urban and rural students. To draw correct comparisons, the urban-rural divide must first be determined, before strata or clusters for sampling are drawn. Therefore, how rural and urban areas are defined will, in turn, affect our measurement of inequality in education.

- *The Cardiac Accessibility and Remoteness Index for Australia (Cardiac ARIA).* The index aims to reflect access to cardiac health-care services in Australia. Using geographic data on road networks, populous areas, ambulance stations, hospitals, remote-area clinics, and other health-care facilities, Clark et al. (2012) modeled the time required to obtain health-care services in all population locations. The index consists of a two-point system: a numeric category that rates accessibility of services after an acute cardiac event and an alphabetical category that reflects accessibility to services after a patient returns to her community.

- *Remote schools in Taiwan.* Elementary and middle schools in Taiwan are classified as 'remote,' 'extra-remote,' or 'not remote' according to recommendations by county education bureaus. These labels are assigned based on thresholds determined by each county individually, depending mostly on schools' height above sea level and access to transportation services. As of 2015, 869 school campuses of public elementary education are classified as remote and 128 as extra-remote. These schools struggle to fill vacancies in both administration (Liu & Chiang, 2013) and teaching (Fan & Chang, 2016; Tsai & Wang, 2016), and policies for either closing them down or attracting teachers and principals are subjects of intense debate (Cheng et al., 2008; Wang & Chen, 2007).

- *The 2003 NCES reclassification.* Following advances in geocoding technology and updates to the 2000 Office of Management & Budget (OMB) definitions of metropolitan areas, the NCES assigned a new set of locale codes that sorts schools into 12 categories based on how their locations are classified by the OMB, with three subcategories for four major locale categories: city, suburban, town, and rural. The classification system was released in 2006, and the first year of data to include the new locale codes was the 2003–04 school year. As a result of the change in locale codes, 8.2% of public schools classified as rural in the former system were no longer considered so under the new classification, and 3.0% of all public schools were newly added to the rural category. This led to a change of rurality status for 5.3% of all students studying at elementary or secondary public schools, and 11.2% of students formerly classified as rural were removed from the category (Provasnik et al., 2007). As eligibility for the Federal Rural Education Achievement Program (REAP), which provides noncompetitive federal grants to rural districts, is partly based on the locale codes assigned to schools within districts, a switch in rurality status implied nontrivial changes in resources for schools and districts.[3]

The existing methods take the intersections or unions of sets obtained through setting thresholds along some prespecified characteristics, often based on location or access to transportation. Although the choice of variables for setting the cutoff points may be intuitive, the omission of socioeconomic characteristics such as income and education levels in the design of classification systems could fail the purpose of directing resources to those in need of assistance.

Aside from the limited nature of sets of thresholds, where a school, hospital or administrative area might fall along the metric can also change due to regulatory arbitrage and market forces of supply and demand. A remote classification produced through transportation-based thresholds, such as distance to the nearest bus stop (schools in Taiwan) and driving time to medical facilities (hospitals in Australia), might change if new transportation facilities are constructed. However, the underlying factors that necessitated the classification of remote areas in the first place (e.g., disadvantages in the learning environment) might not have changed along with the availability of transportation.

A data-driven approach

The major issue with the existing classification method is the use of subjective thresholds on a few variables about the availability of transportation, geographical location, and population size. The larger the set of variables is, the harder it is to accommodate the use of fixed-threshold methods due to the number of dimensions that additional covariates necessarily entail.

Our strategy for improving on the existing method is to consider both the current classification and an extended set of information about local demographics and socioeconomic status, in addition to standard criteria such as geographical location and population size. The empirical goal is to map the comprehensive set of covariates from data onto a continuous score as the remoteness score. For ease of application, we use the standard probit model, the most common method for mapping covariates to a scalar, to construct the remoteness score. The remoteness score is the estimated probability of a unit (e.g., a school or a hospital) being selected into the existing rural classification, conditional on the observable characteristics. Although not necessarily reflecting the rurality of a given unit, the current rural ratings are meaningful for conceptualizing school rurality. As we show below, using the current ratings also provides information on unobservable characteristics of school campuses that are not captured by observed covariates.

Consider that the government classifies campus i as remote in year t if the net social benefit from a rurality label, measured by the sum of the latent index and an observed component, exceeds 0:

$$Remote_{it} = \mathrm{I}\{u_{it} + X_{it}\beta > 0\}, \tag{1}$$

where $\mathrm{I}\{\cdot\}$ represents the indicator function. X_{it} includes the constant term and a comprehensive set of covariates indicating the need for allocation of extra resources (see Table 1 and the Data section). β is a vector consisting of all coefficients. We assume that the allocation of resources is observed and fully captured by X_{it}. The latent index u_{it} is a random variable, representing the combination of all unobserved components unrelated to the need for extra resources, such as residents' attitudes towards education, children's aspirations for their future, or school principals' bargaining power with the government.

The official classification $Remote_{it}$ does not necessarily reflect the rurality of a given campus, as unobserved factors (e.g., school principal's bargaining power or residents' attitude towards education) could also play a role. A campus might have a high latent index u_{it} but the observed component $X_{it}\beta$ might suggest that no extra observable resources are needed from government agencies. As a great value of the latent index cannot indicate the need for additional resources, we assume the justification for remoteness status depends entirely on the observable component $X_{it}\beta$. Thus, the degree of remoteness of campus i in year t is a function of the observed component – namely, the probability of the government classifying that campus as remote given the observables X_{it}.

Assuming that the latent index u_{it} in model (1) is a standard normal random variable, we can estimate the degree of remoteness for each campus i in year t using a standard probit model:

$$\begin{aligned} \Pr(Remote_{it} = 1|X_{it}) &= \Pr(u_{it} > -X_{it}\beta|X_{it}) \\ &= \Phi(X_{it}\beta), \end{aligned} \tag{2}$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution. The propensity score $\Phi(X_{it}\beta)$ is the 'remoteness score' of campus i in year t implied by data X_{it} and existing classification $Remote_{it}$.

Illustration

We apply the proposed approach to constructing the remoteness score for public elementary school campuses in Taiwan. The method can also be applied to education and health data in other contexts. Unlike the Australian or American systems with their multiple categories, the Taiwanese case is more straightforward for purposes of illustration because the official classification system only involves two dummy variables, which separately identify the remote campuses (including extra-remote ones) and the extra-remote campuses.

We first describe the data and explain the method for constructing the remoteness score, and then compare the implied reclassifications with the official ratings.

Data

An advantage of our approach lies in the ease of replicating the procedure in other contexts, a result of its reliance on data that are routinely updated in the public domain of most advanced economies. We assemble a dataset on all elementary school campuses in Taiwan between 2012 and 2015. As the summary statistics and the resulting remoteness score show similar patterns across years, we illustrate our method using data on schools in 2015, as summarized in Table 1. For purposes of policy recommendations, we exclude private schools and those campuses located on islands off the main island, and we count school branches separately from the main campuses, leading to a total of 2,606 school campuses in our dataset.

- *Current rurality label.* The Ministry of Education assigns remote or extra-remote labels on an annual basis and publishes the results on its website. Justifications for rurality labels are typically based on geographic characteristics or transportation, such as height above sea level or distance to the nearest bus station, with the subjective thresholds decided by county or city education bureaus (Tsai & Wang, 2016). In 2015, about one-third of public school campuses were officially labeled as remote and only 5% as extra-remote.

- *Geographic*. We include two campus-specific and time-invariant geographic characteristics: the height above sea level (elevation) and the length of the driving route to the closest train station (calculated using the Google Maps Application

Programming Interface (API)). Our analysis focuses on school campuses on the mountainous main island of Taiwan. The altitude of the schools in our data ranges from 0 to 2,201 meters, scattered over an island a little larger than the state of Maryland. Therefore, we include elevation as our initial spatial measurement, instead of the size of the district, which might be more suitable in larger, flatter countries.

- *Staff shortage.* Taiwanese elementary schools in remote areas struggle to recruit teachers, so staff shortage is highly predictive of needs for additional resources or policy interventions (Fan & Chang, 2016). We quantify staff shortage in each school using the fraction of unfilled full-time teaching positions among the total number of teachers in the previous year (i.e., 2014). This variable is calculated from the teacher data provided by the Ministry of Education. Researchers studying remoteness of areas in other contexts might need to replace this variable with other relevant characteristics.

- *Race.* We include the fraction of students of indigenous descent in the previous year (i.e., 2014) using school-level data provided by the Ministry of Education.

- *Population density.* We include information about school-age population (aged 6–11), elderly population (aged over 65), and total population in the district, all five years ago in 2010. We divide the population size by the area size to derive the population density. The Ministry of Interior Affairs website provides population data by age group and updates them every year. Alternatively, one could include enrollment-related variables, such as school/campus/class size, from the previous academic year.

However, we recommend the use of local school-age population density, instead of an enrollment choice variable, because the population density is easier to obtain.

- *Aging.* To reflect the effects of rapid aging on remoteness classification (Chen, 2012), we control for the five-year population growth at the time of measurement. We include the rates of growth in school-age population, elderly population, and total population at the district level.

- *Education and income.* Ideally, variation in students' backgrounds across schools should be taken into account too, but this type of information is often not available. We proxy mothers' and fathers' average education levels in the district using the ratio of women and men older than 25 who have at most completed middle school (grade 9) to those who have a college degree or more. We further capture the variation in average family income across campuses by conditioning on the district-level median and the interquartile range in taxable income two years ago. We lag income by two years instead of one because of the time it takes to release data generated through tax records. We obtain the district-level income and education data from the websites of the Ministry of Finance and the Ministry of Interior Affairs.

Like studies in various literatures that employ the propensity score, the choice of variables to include in the model depends on the goal of the study. The selection of variables for calculating the remoteness score depends on the purpose of defining rural areas.

Constructing the Remoteness Score

We construct the remoteness score by estimating the standard probit model in equation (2) using Taiwanese public elementary school campus data. The dependent variable is the binary status of 'extra-remote' assigned to school campuses by the government. Although spatial characteristics which government agencies claim to have based their decisions upon are fixed, remoteness designations do change and are subject to discretion (Chen, 2007; Tsai & Wang, 2016). We choose to use the extra-remote status, rather than the remote status, because requirements for the former are more stringent and thus might involve less discretion and a smaller unobserved component u_{it} in equation (2) in the labeling process.

We assume that the official extra-remote labels are informative for assigning labels. The unobservable characteristics in u_{it} might be associated with, for example, the principal of school *i*'s bargaining power with government agencies and the residents' attitudes towards education. These unobserved factors could potentially have played a role in shaping the official classifications, and thus provide information beyond the spatial and socioeconomic variables that we have observed and included in X_{it}.

Table 2 reports the marginal effects of the covariates on the official rurality label, using the standard probit model. To allow the remoteness measure to be related nonlinearly with spatial/socioeconomic variables, we take the logarithm of geographic variables, population size, and income. As the county governments' stated categories are either geographic or related to transportation, it is as expected that the logarithm of elevation or distance to the nearest train station is significant across all specifications. However, adding the fraction of indigenous students to the estimation of probability in column 2 considerably reduces the coefficients of both geographical variables because, other things being equal, the number of indigenous students increases with elevation and with distance from the nearest train station. Furthermore, aborigines are concentrated in districts that are less populous and are aging particularly fast. As a result, after controlling for the local population size and speed of aging, the chance of gaining the extra-remote label no longer increases with a higher fraction of indigenous students in the school, as column 4 shows.

In the full model, we further include variables on income and education in the probability estimation. As column 5 shows, the strongest explanatory power in the full model belongs to the drop in total population in the district (rather than the geographical variables). For every 1% drop in population size in the district, the probability of a local campus gaining the extra-remote status increases by about 0.5 percentage points, and this effect is statistically significant. This explains nearly 10% of the extra-remote labels given that only 5% of campuses are labeled as extra-remote.

In contrast, although the geographical variables are thought to be the most crucial factors for the government in defining extra-remoteness, every 1% increase in elevation or distance only has a small impact on the probability of being labeled as extra-remote, of 0.004 or 0.032 percentage points respectively; the geographical variables both only explain less than 1% of the extra-remote rating.

Comparison of Methods

To compare the differences between the categorization generated using the remoteness score and the current labels assigned by the government, we plot the remoteness score of school campuses and their current percentile in Figures 1 and 2, graphically approximating the empirical cumulative distribution function. Currently, Taiwan has 869 government-designated remote campuses, including 128 extra-remote ones. Figure 1 shows the distribution of campuses that change status between the two methods if we limit the combined number of campuses labeled as remote to the present level (869). Similarly, Figure 2 shows the changes in campus status along the distribution of extra-remote school campuses if we cap their number at the current level (128). The changes in categorization are mostly centered on the cutoff, especially in Figure 1, and Figure 2 shows a much greater variance in the remoteness score.

Columns 2 and 3 versus columns 4 and 5 in Table 1 summarize the campus characteristics for the existing versus proposed categorizations. We compare column 2 with column 4 for campuses considered to be remote by the government versus by the remoteness score, and column 3 with column 5 for those considered to be extra-remote. On average, the remote or extra-remote campuses identified by the government are 13% or 27% (185/213 − 1 or 403/555 − 1) lower in elevation, are 18% or 14% (18/22 − 1 or 37/43 − 1) nearer to the closest train station, and have 2 percentage points (11% − 9% or 20% − 18%) fewer unfilled vacancies for full-time teaching positions. The remote or extra-remote campuses identified by the existing method are more populous and located in districts with richer and more educated adults, compared with those designated by the data-driven method.

Taking the current number of remote and extra-remote campuses (869) as given, Table 3 compares the characteristics for school campuses that are considered remote (including extra-remote) by different methods. All variables included in the analysis for remote and extra-remote schools combined show significant differences in means. Compared with those selected by the official classification but not by the proposed classification, campuses selected by the remoteness score but not by the official rating are in higher elevations, significantly further from local train stations, having more trouble in filling teacher vacancies, and located in areas that are significantly less populous, less well educated, poorer, and had more negative population growth. The proposed method assigns remote status to campuses with fewer students of indigenous descent than the existing method because indigenous districts are more negative population growth than other regions, as column 4 of Table 2 suggested. Overall, our reclassification effort replaces 35% (306/869) of the remote or extra-remote campuses, bringing another 306 into the list.

Table 4 repeats the exercise for extra-remote campuses only. The changes show a similar pattern, except for student ethnicity and population growth. Extra-remote campuses selected using the remoteness score but not included in the current official list receive a markedly higher fraction of indigenous students, and saw significantly less decline in their districts' school-age population, compared with those labeled as extra-remote by the government but scoring below the cutoff in our model. On the other hand, differences in the mean of elderly population growth, total population growth, and the median income between the two groups lose statistical significance when we turn to extra-remote campuses only. The change in the list of extra-remote schools after switching to labeling based on the remoteness score is 47% (60/128), adding 59 schools currently considered to be remote (but not extra-remote) and one nonremote to the list.

Conclusion

We propose to measure the 'remoteness' of locations by estimating a standard probit model of a previous remote classification on a comprehensive set of relevant covariates. This method improves on existing classification methods that use fixed thresholds. We apply the proposed data-driven method to Taiwanese public elementary schools. We reclassify 35% of remote and 47% of extra-remote school campuses, shifting the distribution of schools classified as being remote to those located in less-educated areas or with a smaller and faster-aging population, and to schools with more indigenous students and unfilled teacher openings or further from their local train station.

The proposed classification method has the benefit of ease of implementation. A drawback might be its demand for data. However, most of the required data are publicly available in most economies. Researchers working in other settings will have to rely on expertise and judgment to select covariates that would be relevant in other applications.

Measuring education outcomes in remote areas is difficult. Data sets that rely on international comparisons such as the TIMSS must invariably count on their sampling methods. In regions where children tend not to attend school, or attend small schools, learning outcomes might be overestimated. However, as the urban-rural differences in education are policy relevant, it is essential to continue building evidence on the state of education in remote areas. Such an effort must begin with accurate and up-to-date delineations of rural areas; our method could provide an alternative approach to the problem in many other contexts.

Endnotes

1. For example, the US Department of Agriculture's Economic Research Service (ERS) publishes six datasets on rural area delineations, such as the Rural-Urban Continuum Codes, which classify areas using the metropolitan/nonmetropolitan divide drawn by the Office of Management & Budget and subdivide each category using population

size, degree of urbanization, and proximity to metropolitan areas. These are described on the ERS website: https://www.ers.usda.gov/topics/rural-economy-population/rural-classifications/

2. See Cheng, Chan, & Huang (2008) and Clark et al. (2012) for reviews of policy reports. These governments have posted the definition of remoteness on their websites (e.g., for Australia: http://www.dec.nsw.gov.au/about-the-department/our-reforms/local-schools-local-decisions/reform-agenda/resource-allocation-model/location).

3. See the US Department of Education website: https://www2.ed.gov/programs/reapsrsa/eligibility.html

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Table 1

Descriptive Statistics of Public Elementary School Campuses, 2015

	All public elementary school campuses	Officially labeled as:		Relabeled by:	
		Remote 33%	Extra-remote 5%	Top 33%	Top 5%
	(1)	(2)	(3)	(4)	(5)
Number of campuses	2,606	869	128	869	128
Elevation (meters)	109	185	403	213	555
Distance to nearest train station (kilometers)	11	18	37	22	43
Percentage indigenous students in school, 2014	12%	29%	53%	27%	71%
Full-time teacher vacancy percentage, 2014	9%	9%	18%	11%	20%
District population density, 2010					
school age (aged 6–11)	214	30	6	18	2
elderly (aged 65+)	352	59	14	47	5
total	3,365	478	97	313	34
District population growth, 2010–15					
school age (aged 6–11)	–21.7%	–24.3%	–20.5%	–25.9%	–16.6%
elderly (aged 65+)	10.9%	5.9%	3.3%	4.6%	3.2%
total	–0.4%	–2.0%	–3.0%	–2.7%	–3.1%
Middle-school relative to university-educated population in district					
female (aged 25+)	2.4	3.7	4.9	4.0	5.3
male (aged 25+)	1.8	3.2	4.4	3.4	4.9
Taxable income per capita in district (New Taiwan dollars in thousands)					
median	575	539	531	531	530
interquartile spread	626	536	501	527	489

Note: This table reports the sample mean characteristics of Taiwanese public elementary school campuses in 2015. Branches of schools, often found in mountainous rural areas in Taiwan, are counted separately from their main campuses. Columns 2 and 3 follow the existing categorization and display the characteristics of remote and extra-remote campuses, which account for 33% and 5% of all public elementary school campuses. In columns 4 and 5, we recategorize the remote and extra-remote campuses in the same proportion by remoteness scores. To create the remoteness scores, we use all the covariates listed in this table to implement the probit estimation as in Table 2.

Table 2
Probit Estimation for Constructing the Remoteness Score

Dependent variable = Being currently labeled as extra-remote	(1)	(2)	(3)	(4)	(5)
Log elevation	0.013	0.005	0.006	0.002	0.004
	(0.002)*	(0.002)*	(0.002)*	(0.002)	(0.002)
Log distance to nearest train station	0.060	0.048	0.044	0.034	0.032
	(0.005)*	(0.005)*	(0.005)*	(0.004)*	(0.004)*
Percentage indigenous students in school		0.070	0.064	0.000	–0.014
		(0.008)*	(0.008)*	(0.015)	(0.017)
Full-time teacher vacancy percentage			0.109	0.093	0.088
			(0.023)*	(0.022)*	(0.021)*
Log district population density, 2010					
school age				0.009	0.010
				(0.029)	(0.030)
elderly				0.013	–0.005
				(0.025)	(0.026)
total				–0.043	–0.023
				(0.052)	(0.053)
District population growth, 2010–15					
school age				0.064	0.071
				(0.046)	(0.045)
elderly				0.094	0.101
				(0.109)	(0.108)
total				–0.458	–0.487
				(0.126)*	(0.128)*
Middle-school relative to university-educated population in district					
female					0.007
					(0.005)
male					0.002
					(0.005)
Taxable income per capita in district, 2013					
median					–0.013
					(0.087)
interquartile spread					0.056
					(0.061)
Pseudo R-squared	0.35	0.38	0.43	0.49	0.50
Number of campuses	2,606	2,606	2,606	2,606	2,606

Note: This table reports the estimated marginal effects of geographic, demographic, and socioeconomic covariates on the extra-remote classification. We use the estimation results of the full model in column 5 to construct the remoteness score for each campus. Robust standard errors are in parentheses; 5% statistical significance from *t*-tests is indicated by *.

Table 3

'Remote' Labels Comparison: Official versus Proposed Categorizations

	Remote campus				
Official classification	yes	no	yes	no	Mean difference test
Proposed classification	yes	yes	no	no	(2) – (3)
	(1)	(2)	(3)	(4)	
Elevation (meters)	251	143	66	55	77*
Distance to nearest train station (kilometers)	24	18	7	5	12*
Percentage indigenous students in school	39%	4%	9%	3%	–5 ppts*
Full-time teacher vacancy percentage	12%	10%	4%	8%	6 ppts*
District population density					
school age	12	30	62	366	–32*
elderly	32	73	109	589	–36*
total	213	497	966	5,732	–470*
District population growth					
school age	–23.9%	–29.4%	–24.9%	–18.5%	–4.4 ppts*
elderly	4.2%	5.2%	9.1%	15.0%	–3.9 ppts*
total	–2.5%	–3.1%	–0.9%	1.1%	–2.1 ppts*
Middle-school relative to university-educated population in district					
female	4.5	3.3	2.4	1.4	0.87*
male	3.9	2.5	1.7	0.9	0.78*
Taxable income per capita in district, 2013 (New Taiwan dollars in thousands)					
median	530	534	557	605	–23.2*
interquartile spread	511	555	581	696	–26.6*
Number of campuses	563	306	306	1,431	306

Note: This table reports the sample means of covariates for schools according to the labels of remoteness. Column 1 summarizes covariates among the campuses classified as remote by both the official classification and the proposed method, whereas column 4 reports on school campuses that neither the current government rating nor the proposed remoteness score indicates to be remote. Column 2 includes schools classified as remote using the remoteness score but not by the government; the opposite is true for column 3. The last column shows differences between columns 2 and 3, with 5% statistical significance from *t*-tests indicated by *.

Table 4

'Extra-Remote' Labels Comparison: Official versus Proposed Categorizations

	Extra-remote campus				
Official classification	yes	no	yes	no	Mean difference test
Proposed classification	yes	yes	no	no	(2) – (3)
	(1)	(2)	(3)	(4)	
Elevation (meters)	513	603	279	81	324*
Distance to nearest train station (kilometers)	46	39	27	9	12*
Percentage indigenous students in school	64%	79%	40%	8%	38 ppts*
Full-time teacher vacancy percentage	21%	20%	14%	8%	6 ppts*
District population density					
school age	2	2	10	231	–8*
elderly	6	4	24	378	–19*
total	39	28	162	3,621	–134*
District population growth					
school age	–18.3%	–14.6%	–23.1%	–21.9%	8.5 ppts*
elderly	1.8%	4.9%	5.1%	11.4%	–0.1 ppts
total	–4.6%	–1.3%	–1.2%	–0.2%	–0.1 ppts
Middle-school relative to university-educated population in district					
female	5.3	5.3	4.4	2.2	0.88*
male	4.9	5.0	3.9	1.6	1.07*
Taxable income per capita in district, 2013 New Taiwan dollars in thousands					
median	534	525	528	578	–3.1
interquartile spread	490	487	513	636	–25.9*
Number of campuses	68	60	60	2,418	60

Note: This table reports the sample means of covariates for schools according to the labels of extra-remoteness. Column 1 summarizes covariates among the campuses classified as extra-remote by both the official classification and the proposed method, whereas column 4 reports on school campuses that neither the current government rating nor the proposed remoteness score indicates to be extra-remote. Column 2 includes schools classified as extra-remote using the remoteness score but not by the government; the opposite is true for column 3. The last column shows differences between columns 2 and 3, with 5% statistical significance from *t*-tests indicated by *.

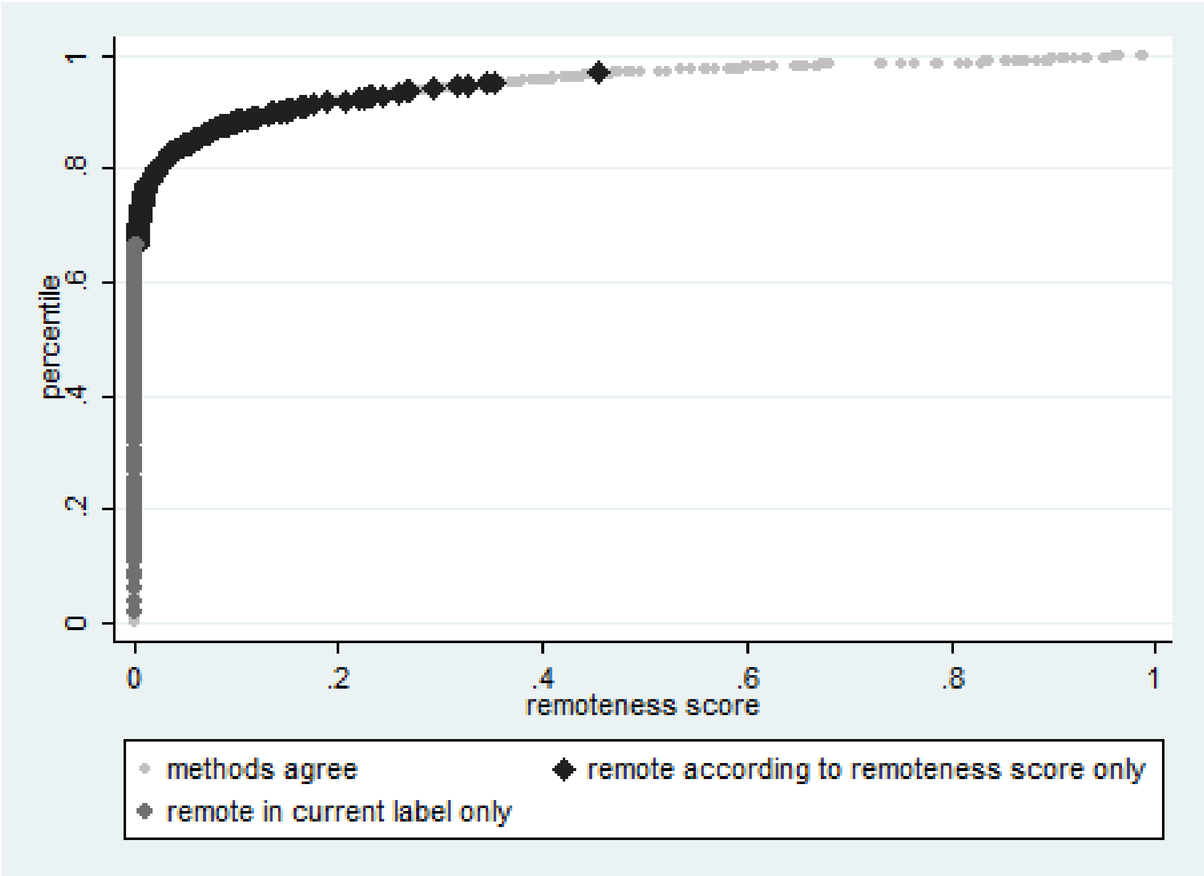

Figure 1. Distribution of Remote Campuses by Categorization Method

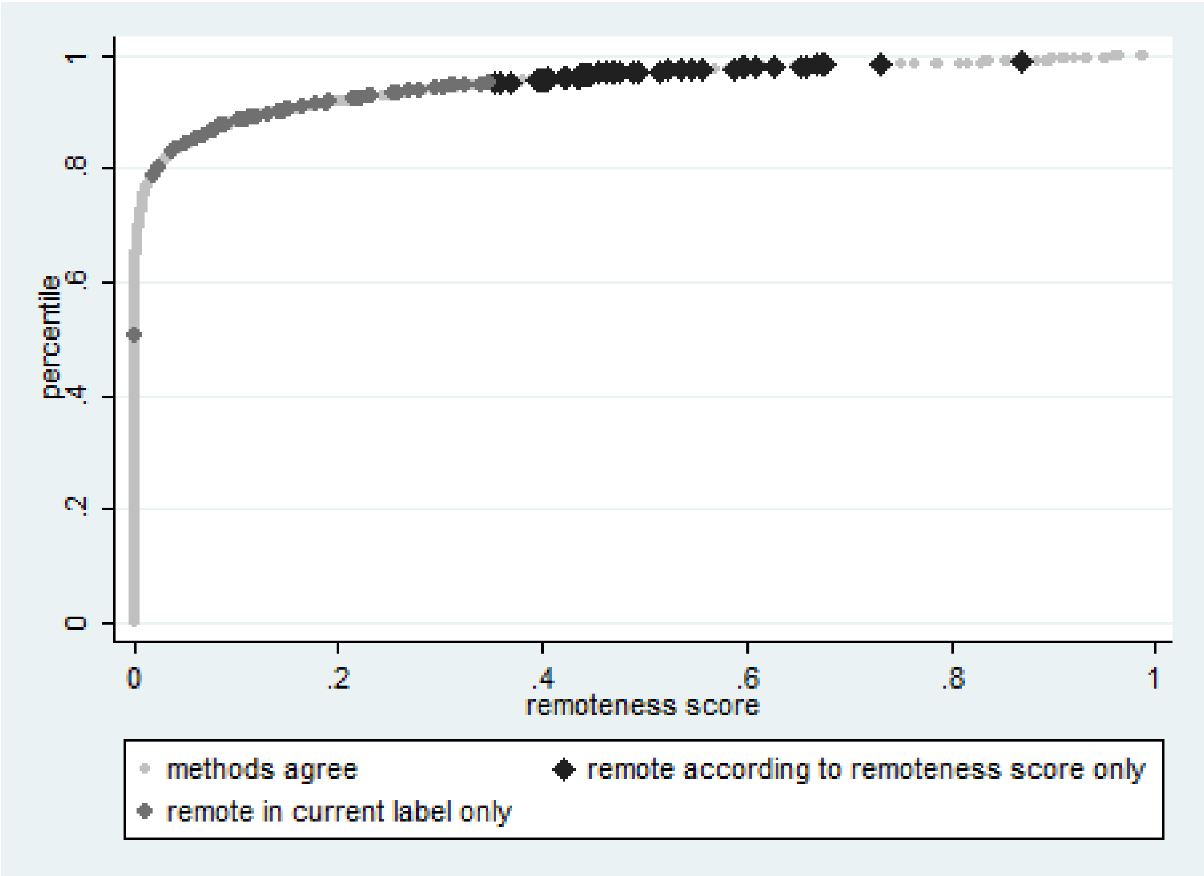

Figure 2. Distribution of Extra-Remote Campuses by Categorization Method